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Brief paper

A feasibility study on the use of anthropometric variables to make muscle–computer interface more practical

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ABSTRACT

High classification accuracy has been achieved for muscle–computer interfaces (MCIs) based on surface electromyography (EMG) recognition in many recent works with an increasing number of discriminated movements. However, there are many limitations to use these interfaces in the real-world contexts. One of the major problems is compatibility. Designing and training the classification EMG system for a particular individual user is needed in order to reach high accuracy. If the system can calibrate itself automatically/semi-automatically, the development of standard interfaces that are compatible with almost any user could be possible. Twelve anthropometric variables, a measurement of body dimensions, have been proposed and used to calibrate the system in two different ways: a weighting factor for a classifier and a normalizing value for EMG features. The experimental results showed that a number of relationships between anthropometric variables and EMG time-domain features from upper-limb muscles and movements are statistically strong (average $r = 0.71 - 0.80$) and significant ($p < 0.05$). In this paper, the feasibility to use anthropometric variables to calibrate the EMG classification system is shown obviously and the proposed calibration technique is suggested to further improve the robustness and practical use of MCIs based on EMG pattern recognition.

1. Introduction

Muscle–computer interfaces (MCIs) based on surface electromyography (EMG) recognition have been rapidly developed for various applications, i.e., prosthesis and electric-power wheelchair, in the last few years (Ahsan et al., 2010; Oskoei and Hu, 2007; Peerdeman et al., 2011; Phinyomark et al., 2011a). Nearly all previous works on EMG-based MCIs focus on classification accuracy improvement and the number of discriminated movements (Hariharan et al., 2012; Ju et al., 2011; Oskoei and Hu, 2007; Phinyomark et al., 2011a; Wojtczak et al., 2009). The success rate of these interfaces is usually higher than 80–90% based on recognizing several common tasks such as the movements of flexion/extension and abduction/adduction (Peerdeman et al., 2011). In laboratories, the number of discriminated tasks, i.e., grasping and wrist motions, has increased to cover most activities of daily living (ADLs) and to control a multiple DOF prosthesis (Cipriani et al., 2008).

While this interface holds so much potential, a few works have given attention to the context of real-world requirements such as long-term use or EMG's uncertainties, i.e., EMG electrode location shift (Tkach et al., 2010) and variation in muscle contraction between days (Phinyomark et al., 2012a), compatibility, i.e., minimal or no need for calibration and training between subjects (Saponas et al., 2010), and robustness, i.e., noise (Phinyomark et al., 2009). Among these requirements, the development of calibration and training issues is still far from being a practical one (Cannan and Hu, 2011; Saponas et al., 2010). In this study, we aimed to address these challenges with special emphasis on EMG and anthropometric techniques that can automatically or semi-automatically calibrate a system.

Due to different body compositions between users, EMG-based MCIs has never really reached the general population (Cannan and Hu, 2011). Every user has different types of muscles with varying sizes and other characteristics, so currently the systems still require new calibration and training (between users and also between days) to compensate for discrepancies. Moreover, this limitation prevents the development of standard interfaces that are compatible with almost any user.

In order to reduce the need for new training and calibration, some useful information should be added as automatic training

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input parameters. For a simple system that uses thresholding techniques, maximum voluntary contraction (MVC) alone is used and may be enough to adapt a system from one user to another. Based on the finding in several related works about a relationship between features of EMG and force, estimating the users MVC can be used to normalize the EMG signals or adjust the threshold values (Bolgla and Uhl, 2007; Vera-Garcia et al., 2010).

However, this relationship is strong only in an isometric or static contraction (Kamavuako et al., 2009), which can be linear or non-linear. When the muscle is free to change length and the joint is free to move as a dynamic muscle contraction, the relationship of EMG features and forces is more complicated (Oatis, 2008). Although force, or MVC, certainly plays a role, it is not significant enough to be used alone in adapting advanced EMG systems, and other additional useful information is necessary.

We know that muscle size, consisting of cross-sectional area (CSA) and length, can be employed together with EMG signal in order to determine muscle force (Hof et al., 1987). This relationship can be explained by the equation of Marras and Sommerich (1991) as shown in Appendix A. It means that there are correlations between muscle size, muscle force, and EMG signal (Raez et al., 2006; Ray and Guha, 1983). Hence, anthropometric variables, a measurable characteristic of the body, are considered. These variables can roughly estimate some muscle-size characteristics such as estimating thigh muscle cross-sectional area by segment circumference (Housh et al., 1995). On the other hand, measuring anthropometric variables is easier and some variables can be measured directly together with EMG signal via armband (Cannan and Hu, 2011; Saponas et al., 2009).

One of the related anthropometric variables is forearm circumference, which can be measured automatically via a wearable device. Cannan and Hu (2011) used forearm circumference for estimating MVC in order to calibrate the EMG thresholding technique based on the linear relationship between grip strength and forearm circumference as presented in Anakwe et al. (2007). However, the relationship between EMG during MVC and forearm circumference is not strong as found with grip force, and further anthropometric variables are recommended to be incorporated to make a reliable adaptive system (Cannan and Hu, 2011).

In this paper, the relationship between common-used EMG time-domain features and related anthropometric variables is investigated. As mentioned, features of the EMG signal were used to find the correlation instead of EMG associated with 100% MVC because we would like to move from calibrating the simple thresholding techniques to machine learning and pattern recognition. It should be noted that feature extraction is used as an input vector for classifier to make a decision output (Phinyomark et al., 2012b). So actions associated with EMG signal, e.g., forearm pronation/supination and hand open/close (dynamic contraction), are also used instead of EMG isometric (static) contraction.

Every strong and significant association between EMG feature and anthropometric variable, found in this study, could benefit a further design of EMG systems. It could automatically adapt the setting to a wider population. Moreover, due to a rapid increased number of wearable devices, anthropometric variables would become more practical and important in the near future.

2. Material and methods

The EMG data, which were used to investigate the relationship between anthropometric variables and EMG features in this study, were recorded from eight movements, five positions and twenty subjects during four days.

Eight movements consisting of forearm pronation (FP), forearm supination (FS), wrist extension (WE), wrist flexion (WF), wrist radial deviation (WR), wrist ulnar deviation (WU), hand open (HO), and hand close (HC) were chosen based on the frequently used in MCIs studies (Oskoei and Hu, 2007; Peerdeman et al., 2011; Phinyomark et al., 2011a), as shown in Fig. 1. These are movements of hand, wrist and arm. In addition, the shoulder was positioned at 0 degree (neutral) with elbow in full extension.

EMG recordings from five muscles were selected from both upper-arm and forearm and from both flexor and extensor muscles. The amplitude shape of EMG signals acquired from all muscles was significantly different according to the direction of eight movements as shown in Fig. 2 (Phinyomark et al., 2011b). There were: extensor carpi radialis longus (ECRL), extensor carpi ulnaris (ECU), extensor digitorum communis (EDC), flexor carpi radialis (FCR) and biceps brachii (BB), as shown in Fig. 3.

Twenty healthy subjects participated in the experiment consisting of 10 males (M1–M10) and 10 females (F1–F10). The age of the male subjects was 21.5 ± 0.97 years and of the female subjects was 21.2 ± 0.79 years. All subjects were dexterous with their right hands. They signed an informed consent in accordance to the University

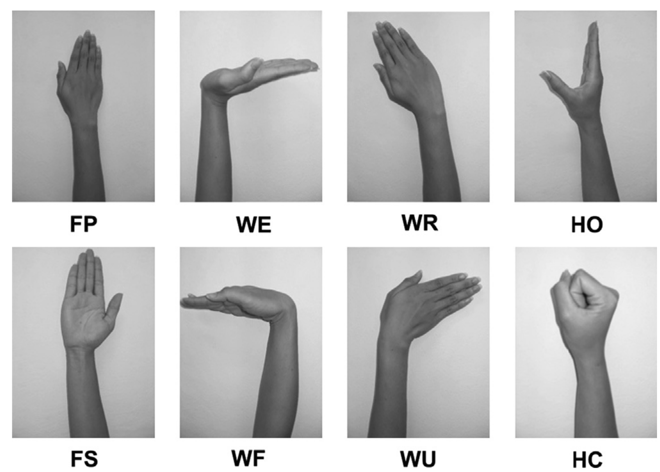

Fig. 1. Eight upper-limb movements.

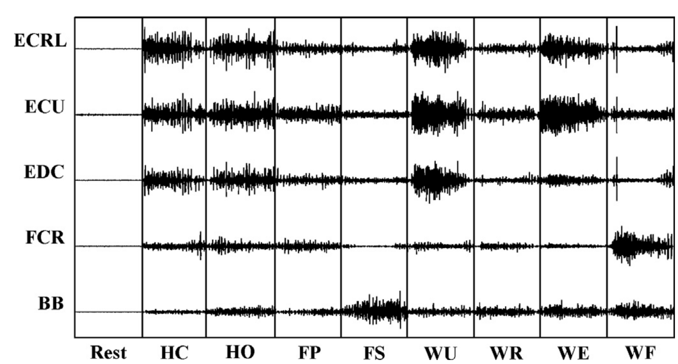

Fig. 2. The example amplitude shape of EMG signals acquired from five muscles and eight movements with rest state.

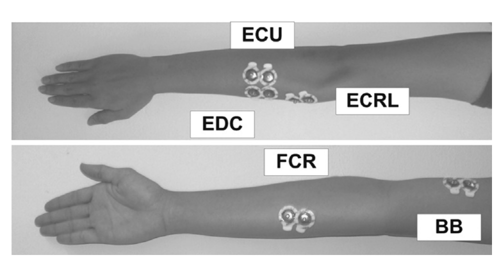

Fig. 3. Five electrode positions.